Optimizing Tesla Supercharger Locations in Virginia: Comparison of Solving a P-Median Problem

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ABSTRACT

Electric vehicles are becoming a recent popularity. Tesla Motors currently holds the market share being the most popular electric vehicle in the United States. With its Model-S and now more affordable Model-3 they are becoming more common place on the roads in the United States. One major limiting factor further adoption is the perceived lack of range a electric vehicle can, have that can cause "range anxiety". One way to remedy this is to have charging stations that can quickly charge to reduce "range anxiety". Tesla has a network of fast chargers called Superchargers, and are currently expanding even further. Currently the state of Virginia has 11 Superchargers spread out throughout the state. Even with these chargers, their current spread can make long distance travel tedious within Virginia. Currently five new Superchargers are proposed for the end of 2018 within Virginia with set locations within counties. This paper will explore how to optimally place these five new Superchargers in comparison to Tesla's choices based on current fast charging stations, and their distance, and population that the demand needs to meet.

Categories and Subject Descriptors

G.2.2 **[Discrete Mathematics]:** Graph Theory—*graph algorithms, network problems, p-median*
D.3.3 [**Programming Languages**]: Python

Keywords

Python, P-Median, ArcGIS, Graph Theory, EV

1. INTRODUCTION

Electric vehicles have been steadily gaining popularity throughout the United States. The Energy Information Association (EIA), has shown that there has been an increase sale of electric vehicles and further potential growth in the future (2017). Tesla Motors Inc. has the highest adoption of electric vehicles in the United States with its sale of the Model-S[1](McCarthy, 2017). A Tesla Model-S pricing begins at $60,000 USD, which is relatively expensive for a car. Even the Model-S's high price point it has become a leader in electric vehicles in the United States. Tesla has recently introduced a more affordable Model-3 which also has a high adoption rate. Currently issues through logistics and shipping are limiting the amount of Model-3's delivered (Hull, 2018). With the issues in delivery of Model-3's there is still a large demand and long preorder line. With the higher rate of adoption of these vehicles, more convenient charging stations are needed. Jia et al. (2012), explains that development and adoption of electric vehicles and charging stations should be considered in conjunction. The availability of charging stations can influence whether a consumer purchases an electric vehicle and how a current consumer utilizes their electric vehicle.

One of the main limiting factors of more prevalent adoption of electric vehicles is range of battery (Mangram, 2012). Even as electric vehicles range increases and a larger network of charging stations are created, there still a term noted throughout the literature of "range anxiety" (Mangram, 2012). Range anxiety is the issue a consumer feels due to the lack of infrastructure to charge their vehicle, the perceived limited range of a battery, and the charge time of a battery. The lack of infrastructure itself is a limiting factor because it is not convenient for someone to have an electric vehicle (Yilmaz et al. 2013). According to Yilmaz et al. the best way to combat range anxiety outside of a more robust charging infrastructure, is to have fast (or level 3) charging stations. With these fast charging station, range anxiety can be reduced because consumers have the ability to charge their vehicles quicker. Charging an electric vehicle can vary depending on the type of charging capabilities a station has. One of the ways to alleviate range anxiety is to have access to fast chargers (Botsford & Szczepanek, 2009). If you utilize a home charger which has the lowest tier of charging output, it can take 3-5 hour to charge your vehicle (Frade, 2011). Whereas if you use a fast charging station it can take 20-30 minutes to charge a vehicle's battery (Frade, 2011). Speed is contingent on battery size, and current charge capacity of charger. The general concept is the highest tier chargers or fast chargers are more convenient and can close the gap on range anxiety for consumers.

Tesla provides fast charging stations through the United States which dramatically cuts down charging time[2]. They are limited to the use of Tesla vehicles but provide free usage for most Tesla vehicles[3]. Although some models give a limited allowance of usage with their Supercharger network, they still advertise charging to cost less than traditional gasoline if required to pay. As mentioned before Tesla currently has the market share and

[1] https://www.tesla.com/models Telsa's Model S

[2] https://www.tesla.com/supercharger , Telsa's superchargers network

[3] The charging credit is unlimited if you purchased your vehicle before 2017 and it is a Model-S or X, whereas if you bought it after this date you have a 1000-mile credit.

highest adoption of electric vehicles. Along with its widespread network of 1,191 Superchargers throughout the United States. The benefits of owning a Tesla vehicle seems like the best choice in terms of electrical vehicle purchases. The purpose of these Superchargers are for long distance travel though. They are intended to be convenient forms of re-charging a Tesla in long trips. This is Tesla's intention with limiting how much you can use them and limiting usage with allowances. One of the biggest issue with utilizing a fast charging station for electrical vehicles constantly is the stress it can place on a lithium battery. It can degrade much quicker as you fast charge, and reduce the longevity of it (Ansean et al. 2013). Fast charging is convenient but it's not meant to be utilized as an everyday method to recharge current batteries in electric vehicles.

Currently Virginia has a total of eleven Superchargers within it, with the plan to build five new ones[4]. With the current eleven it can be difficult to travel within Virginia conveniently based on their distances. The new five locations can improve long distance travel within Virginia along with outside states that are traveling within Virginia. The new locations for the three are within Fairfax, Gainesville, Newport News, Tysons, and Arlington. This gives an opportunity to locate and find the optimal placement of them based on distance and population, and compare them with Tesla's choices.

The purpose of this research is to find the optimal placement of these future Tesla Superchargers within Virginia using constraints of current charging stations distances and the population of Virginia counties. This paper will utilize the whole state of Virginia as a case study, due to the future planning of Superchargers. This will be an interesting take to see where these Superchargers might actually be placed in conjunction to this research's optimal placement. The constraints used in this research is the distance from each current Tesla fast charging station, and the median population center of each county within Virginia. The overall motivation of this research is to better aid the electric vehicle adoption and close the gap of "range anxiety", which is especially prevalent in long distance travel. Using Tesla's Supercharger was chosen because of the current popularity of them and having a wider consumer base.

Having optimal placement of faster charging stations can greatly improve the current infrastructure of the Superchargers within Virginia but also long distance travelers outside of the state that might utilize them. The optimal placement of the Superchargers will be posed as p-median problem, we will be using distance and population demand as constraints of this P-median formulation. The distance constraint will be from current superchargers and potential ones, along with demand points. The main method will be using the Python PuLP library to solve this question, and comparing to ArcGIS Pro's output of the same problem. This research paper's goal is to answer the following questions:

(1) *What is the optimal placement of the five future Superchargers using PuLP library and ArcGIS Pro?*

(2) *How does it compare to where Tesla chose their five locations?*

[4] This is according to Tesla's current supercharger network and where they plan on building the new ones. https://www.tesla.com/supercharger

2. LITERATURE REVIEW

Placing facilities in an optimal location is not a new problem, nor is it when dealing with charging stations for electric vehicles. As mentioned before this problem is referred to as a p-median problem. P-median purpose is to find the optimal placement of future facilities based on demand of current locations (Laporte, 2016). The precise location of the optimal placement is very difficult to know precisely due to the p-median problem being an NP-hard problem (Mihelic & Robic, 2004). We are not expected to find the exact solutions of these locations (Mihelic & Robic, 2004). But we can get close with constraints that narrow down the choices of the optimal locations, but this also can give varying answers depending on the constraints chosen.

Research in the past has utilized different methods and formulation to solve the p-median problem, introducing different constraints. Although not all literature uses a strict sense of p-median problem, they related by finding optimal location. The main themes of the literature are the consideration of the electric grid and charging stations, the types of constraints used to pick the optimal location, the models used, and effect on pollution along with other forms of energy.

2.1 Electrical Grid & Charging Stations

The discussion of the electrical grid is an area is a common recurrence within literature. Frade et al. (2011), highlights how the electrical grid is important to utilize fast charging. Something that is needed for the Tesla Superchargers, which utilize a form of fast charging by directly connecting to the power grid infrastructure of an area. This is something that will not be utilized as a constraint for this research due to limited data on the power grid of Virginia. However, there is still utility in finding optimal placement without the constraint of the electrical grid (Jia et al., 2012). It can reduce the cost of planning and help narrow optimal location of where to place chagrining stations (Jia et al., 2012). Although it is important to note that there is potential stress on the electric grid having a charging station especially a fast charging station (Weiler, 2011). A charging station can increase the load and stress on a electrical grid, which can affect the residents and businesses of an area. With this current paper's study of placing the Tesla Superchargers there is still value in finding the optimal location utilizing the constraint of current Supercharger stations. It can help plan and place them to close to the optimal areas that have access to the electrical grid of individual counties in Virginia.

Frade et al. (2011), also mentions the stress of increase power usage of a fast charging station can have, along with increase cost of a higher power output charging station. This can place greater importance on how many fast charging stations you will have in a given area, especially with a smaller case study like Fairfax county. Sometimes the choice is not whether to place a fast charging station but a slow charging based on how an area functions (Frade et al., 2011). This research will focus on fast charging though, specifically the future Superchargers locations in Virginia. The reasoning is because the current network of superchargers can make long distance travel tedious and difficult within Virginia and traveling into Virginia. Adding five new stations will be a great benefit to Tesla owners traveling in Virginia. But they can be underutilized if they are not optimally placed.

Another factor to consider is access to the charging stations. One area is the access to public or private entities. Some charging stations are restricted in the case study of Lisbon, Portugal. Public and private access is one restriction along with only being available during certain times of the day (Frade et al., 2011). The same can be said about Virginia's current charging stations data set, they are limited to certain people such as employees of a company, or guest of a hotel along with limited hour usages. The Supercharger themselves are limiting because only Tesla brand vehicles can utilize them. Although this paper will not look at the how restricted access has an effect on optimal location, it will be an interesting factor to look into the future.

Mentioned previously, there is "range anxiety" attributed to ownership of electric vehicles. The inclusion of fast charging can eliminate that anxiety, along with increasing the reach and range of how someone utilizes a vehicle (Botsford & Szczepanek, 2009). Botsford & Szzepnek (2009), utilize and example of how a fleet of service vehicles increase the area they serviced due to the placement of a fast charger allowing them to reduce "range anxiety". Although this research will not look into how range anxiety will change with the optimal placement of Superchargers it will aim to reduce it by optimally placing Superchargers. Seeing if it will actually affect range anxiety is something this paper will not focus on. Increased range can change the dynamic of who travels within and out of a state, and which parts of a state. So it is important when optimally placing a placing facilities to understand what population you are serving and not to be overserved or underutilized.

2.2 Constraint Choices

When modeling a location problem, what determines the placement of infrastructure depends entirely on the constraint you choose. The constraints can be simplistic to very complex having many different variables in order to model the optimal location of charging stations. But the constraints also matter for what you are optimizing for.

Jia et al., (2009) have numerous constraints ranging from the number of charging stations, the power rating, operating factors etc. With these constraints you can model a very precise optimal location of charging stations. Due to the limited scope of this research paper the main constraints will be distance of current Supercharging stations, and the population of each county.

An interesting constraint used is by Frade et al., (2011), is the daytime and nighttime demand of people. This can be very useful to model and understand where to place it based on commute times of people or how an area functions such as if it is a late night taxi hub. Specifically Frade et al., (2011) takes into account the employment population of Lisbon and the night and daytime usage of chargers.

Upchurch et. al (2009), utilizes population as a constraint along with the flow of traffic. Frade et al., (2011), also utilize population specifically the employment population. Population demographic is something that will be used in this research. Specifically using the 2010 Census population count of each individual county in Virginia and Creating mean center point for each county. Considering population is extremely important to understand where the demand for Superchargers or similar facilities can be.

Upchurch et. al (2009) focuses their study area to the state of Arizona, and Frade et al., (2011) is focused to a small study area of a neighborhood in Portugal. Both these papers utilize a focused study area, where one is a whole state and another is a smaller subset of an area. The study area of this paper will focus similar to Upchurch's on a whole state using Virginia case study. The Arizona case study creates an abstraction of the network of roads and population centers to understand population flow, and where to place optimal locations (Upchurch et al., 2009). It is important to note Upchurch et. al, (2009) uses "alternative-fuel stations" that aren't strictly electrical charging stations, but this model could be utilized for charging stations for electric vehicles. Frade et al., (2011) model is much more detailed focusing on the small neighborhood of Lisbon, Portugal. Parking spaces and a precise network of roads are considered through the paper (Frade et al., 2011). This specific research is a more of a converge of Upchurch et al. (2009) and Frade et al., (2011) papers, where the focus is not very broad or very specific. Something that is not currently present in literature is simplistic model but focusing medium sized area, such as a state in the United States using strictly electrical charging stations. This paper will breech into a different area of past research along with the possible comparison of where actual locations of Superchargers will be placed, and this research projects optimal placement. This research will not have a direct impact on the actual chosen locations of the Superchargers within Virginia.

2.3 Models and Method Utilized

The models utilized in papers are similar or an extension of the p-median problem. The basis of each model is that they are using constraints to find the optimal location of charging or fueling stations. They are looking for a location that meets the highest demand with the lowest cost (which is not the center point of other points always). Methods differ from using specific software, or programming languages, or not being mentioned at all.

Jia et al. (2009) utilizes a software called CPLEX[5], that is a type of optimization software to create their model for optimal place. CPLEX is an optimization software created by IBM that is used for optimization and linear programming problems. Just from examining the constraints Jia et al. (2009) used the user can create very complex models with it. Frade et al. (2011) model and methods are not explicitly stated but the goal of their model is to optimize maximum cover along with having day and night time demand as a constraint. Frade et al. (2011), model is similar to most p-median problems in the formulation of the math, there is a maximization and constraints the maximization is subject to

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Annamali et al. (2017) are very detailed in their explanation of their model using p-median and python. They provide source code and example of a p-median problem solved (Annamali et al., 2017). This paper will model will be similar to Annamali et al. (2017) in the utilization of python, but with the goal of finding optimal placement of Superchargers based on current fast chargers.

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https://www.ibm.com/analytics/data-science/prescriptive-analytics/cplex-optimizer

2.4 Pollution and Petroleum Dependence

Prior research tends to mention the reliance of petroleum products, the impact of pollution and how electrical vehicles can alleviate it. Although this current research paper is not focusing on the impact of pollution and vehicles, the fact other papers attribute to motivation makes it an important point to note. The common trend within prior research is the effect of pollution and why their research is important.

Frades et al. (2011), briefly mentions emissions and the reduction of them with electric vehicles. But a more interesting point is noise pollution and how electric vehicles are much quieter than their combustion engine counter parts (Frades et al., 2011). It is the only paper that mentions the impact of noise pollution and advantage of electric vehicles. Unchurch et al. (2009), mentions pollution along with oil prices to as a driving force to optimize alternative fuel source locations.

The mention of the pollution and petroleum products is mentioned sparsely throughout the literature. There is no strong focus on the effects and impact of them. The current research paper will not focus on the impact of pollution and other forms of transportation. Although this research acknowledges the movement towards electric vehicles can be attributed to similar conclusion as prior research.

3. METHODS

To solve this optimization problem, the problem will be formulated as a p-median problem. The constraints will be the distance between current fast charging locations in Virginia, along with the population of each county as the second constraint. The goal is to find the optimal placement of the new Tesla Superchargers in context of the current fast charging location. The p-median problem will be solved using, a non-weighted distance matrix which does not include the population, and a weighted distance matrix which does include the population. The distance calculation will be using Euclidean distance for python, and the built in network distances within ArcGIS Pro. The choice of using Euclidean distance is not an arbitrary reason. According to Gonçalves et al. (2014), using Euclidean distance in solving p-median or similar optimization problems does not make solutions less optimal or differ from utilizing a Manhattan or road network distance.

Another facet of this goal of this research project is to utilize python, specifically the PuLP library[6]. PuLP is a python library that can be used for optimization and linear programming problems. The benefit of PuLP is that is free and open source way to solve complex problems (Mitchell et al., 2011). Because of it is open source more advanced users can manipulate the library to their problems and how they want to solve them (Mitchell et al., 2011). The reason for utilizing python a library versus a Geographic Information System (GIS) software, is for flexibility of python and not to limit future research and limit to a cost restricted software. But the results will be compared to a GIS software. Similar to Annamalai et al. (2017), utilizing of python to solve P-median problem, of the facility centers based on distance of current facilities. Where this problem differs is it has a set number of locations which is five. Also the purpose of this research is not to find center points, as Annamali et al. (2017) did. Finally, we will also solve the same p-median problem using ArcGIS Pro[7]. This is because ArcGIS Pro has a built in p-median solver, and gives the opportunity to compare the Python results to a commercial software results.

3.1 P-Median Formulation

In order to solve the current problem as a p-median problem we need to formulate the problem with the objective function of what we are solving. To narrow our choices we have constraints that limit the objective function. In this p-median problem we are minimizing the distance the demand points will have to travel towards the Superchargers.

$$d = shortest\ distance\ from\ node\ i\ to\ node\ j \quad (1)$$
$$h_i = population\ demand\ at\ node\ i \quad (2)$$
$$p = the\ number\ of\ facilities\ that\ are\ to\ be\ located. \quad (3)$$

Objective Function:

$$Minimize \sum_{j \in J} \sum_{i \in I} h_i d_{i,j} Y_{i,j} \quad (4)$$

Constraints:

$$\sum_{j \in J} Y_{i,j} = 1, \ \forall i \in I (5)$$

$$Y_{i,j} - X_j \leq 0, \forall i \in I, j \in J \ (6)$$

$$\sum_{j \in J} X_j = p \ (7)$$

$$X_j \in \{0, 1\}, \ \forall j \in J \ (8)$$
$$Y_{i,j} \in \{0, 1\}, \ \forall i \in I, j \in J \ (9)$$

$$Y_{i,j} = \{1, \ if\ demand\ node\ i \in I\ assigned\ to\ supercharger\ located\ at\ j \in J \ \ 0, \ otherwise \ (11)$$

$$X_j = \{1, \ if\ supercharger\ located\ at\ j \in J \quad 0, \ otherwise \ (12)$$

The shortest distance (1) is the shortest distance from each current Supercharger station in Virginia and the demand nodes which are the mean center nodes, and the possible new Supercharger locations which are also the mean population center for each county. For P (3) the number of facilities we are locating are 5, so P=5, but within Python and ArcGIS, we are actually solving for P= 16. This is because we are considering the current 11 locations in Virginia we do not want them to be chosen as new nodes, but they can still meet the demand of current population nodes.

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[6] https://pypi.python.org/pypi/PuLP the python PuLP library for linear programming.

[7] https://pro.arcgis.com/en/pro-app/

Although the formulation is P=16, this will only choose 5 new Supercharger locations and the previous 11. The minimize function (4) is overarching formula to solve in order to minimize the distance of the new and old Superchargers to the demand nodes. The first constraint (5) will direct each demand node to a single Supercharger, so a demand node will not be able directed towards more than a single one. The next constraint (6) highlights that only a Supercharger node can accept a demand node, a demand node cannot accept another demand node. The P value constraint (7) is similar to what was discussed before we are solving for the P=16, by choosing P=16 we are solving for 11 of the current existing Superchargers, and 5 new Superchargers. Constraints (8) and (9) are the binary values of the demand nodes, and the Supercharger nodes. For the existing 11 nodes they are assigned the value of 1 beforehand. The value of 1 will determine if a Supercharger location will be chosen, and which demand node will be attributed to a Supercharger location. It is important to also note the adding the population weight in the origin and destination-matrix does not change the formulation, only the data values of the matrix changes.

3.2 Python

As mentioned before this research papers goal was to solve the p-median formulation for this problem using Python's PuLP Library. But beyond that was to solve the included precursor steps to solve the P-median problem. As highlighted in Fig 1. were the steps taken in order to solving the problem using Python

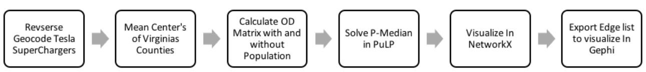

Figure 1. Steps Taken to Solve P-Median in Python

The Tesla Supercharger were geocoded using the addresses from Tesla's Website, with Google Map's API. The mean center of Virginia's counties were the only step where an ancillary piece of software (ArcMap) was necessary in the Python method. With Python the origin and destination (OD) matrix was created using a haversine formula shown in code snippet Fig 2. to give distance similar to a Euclidean distance.

```python
def spherical_dist(pos1, pos2, r=3958.75):
    pos1 = pos1 * np.pi / 180
    pos2 = pos2 * np.pi / 180
    cos_lat1 = np.cos(pos1[..., 0])
    cos_lat2 = np.cos(pos2[..., 0])
    cos_lat_d = np.cos(pos1[..., 0] - pos2[..., 0])
    cos_lon_d = np.cos(pos1[..., 1] - pos2[..., 1])
    return r * np.arccos(cos_lat_d - cos_lat1 * cos_lat2 * (1 - cos_lon_d))
```

Figure 2. Code Snippet of Haversine Formulation.

The distance values were double checked using straight line distances using Google Maps. Using the PuLP library allowed the p-median formulation to be set up as a linear programming equation setting up the constraints and to read the OD-matrix, a brief look at the code is shown in Fig. 3. There was also utilization of the NetworkX python library and Gephi network software to visualize the outputs of the p-median problem.

```python
p = 16 #  number of locations to optimize to

# decision variables
# This is same as X = LpVariable.dicts('X_%s_%s', (location), cat = 'Binary', lowBound = 0, upBound = 1)
# but shorter and a format speficier is not needed.

# declare facility variables
X = LpVariable.dicts('X',(facilities),0,1,LpInteger)

# declare demand variables
Y = LpVariable.dicts('Y', (demand,facilities),0,1,LpInteger)
```

Figure 3. Code Snippet of P-Median Formulation

3.3 ArcGIS Pro

ArcGIS Pro has the benefit its is very plug in play with data and solving P-median problems. In the prior step utilizing python the data collection and cleaning allowed and smooth transition into ArcGIS Pro. The Location-Allocation solver in ArcGIS Pro lets you specifically solve a P-median problem, and gives a lot of flexibility in choosing the constraints, which were modeled after the Python formulation.

4. DATA

The electric charging dataset was downloaded from the U.S. Department of Energy (DOE) where they provide a download of all the Alternative Fuel Locations[8]. The Department of Energy, allows a user to download a subset of the alternative fuel locations, such as hydrogen, or electric fueling stations. But does not allow you to download for a specific area so the whole of the United States electric charging stations was downloaded. It also did not include all of the current Tesla Supercharging stations within the United States. This is where the geocoding of the current Supercharger stations were needed in order to pull all the location data of the stations within Virginia. There is a total of 11 Supercharger stations in Virginia that were geocoded obtaining the latitude and longitude for each location. The population data is the total count of people per county from the 2010 Census (Census Bureau, 2011). In order to utilize this data, the population was transformed into mean center values for each county within Virginia. Within ArcMap the latitude and longitude were calculated also, and then exported as CSV file. There is a total of 134 mean center points within Virginia, which will be the demand nodes in the formulation and the potential future locations of Superchargers.

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8 https://www.afdc.energy.gov/stations/#/find/nearest

5. RESULTS

5.1 Python Method

Using the Python Method to solve the p-median problem the five supercharger locations chosen differed for weighted and unweighted values. For the distance only constraint problem, the counties chosen as candidates where Henry, Hampton, Middlesex, South Hampton, And Norton. Whereas for the weighted with population, Martinsville, Russell, Gloucester, Stafford, and Price William were chosen as seen in Table 1.

Tesla Choices	Python Unweighted	Python Weighted	ArcGIS Pro Unweighted	ArcGIS Pro Weighted
Fairfax	Henry	Martinsville	Norton	Fairfax
Gainesville	Hampton	Russell	Richmond County	Roanoke City
Newport News	Middlesex	Gloucester	Appomattox	Newport News
Tysons	Southampton	Stafford	Franklin	Russel
Arlington	Norton	Prince William	York	Pittsylvania

Table 1. Results of Solving through Python, ArcGIS Pro, and Tesla's choices

A visualization of where the Superchargers are located and the amount of demand nodes they receive show that weighted and unweighted points are somewhat similar in terms of placement. Both visualization (Fig. 4 & Fig. 5) mimic the shape of Virginia by locating the points to similar geolocations. The larger and darker hued nodes have more demand points they cater to. The demand they meet though differ especially in the middle of Virginia. Where the unweighted solution has a center supercharger that meets the demand of many points. Whereas the weighted version meets the demand of with two Supercharger points to split the demand show in Fig 4. None of the choices in either solution matched Tesla's choices of future Supercharger locations.

In Fig. 5 the visualization represents the network of the chosen Superchargers and current Superchargers in an abstraction of the major road networks of Virginia for the weighted formulation. The connections are arbitrary and intended to mimic the major highways and interstates of Virginia, the travel between nodes is not limited to the connection displayed in the network. The purpose is to give an idea how the network of Superchargers will change with these possible choices.

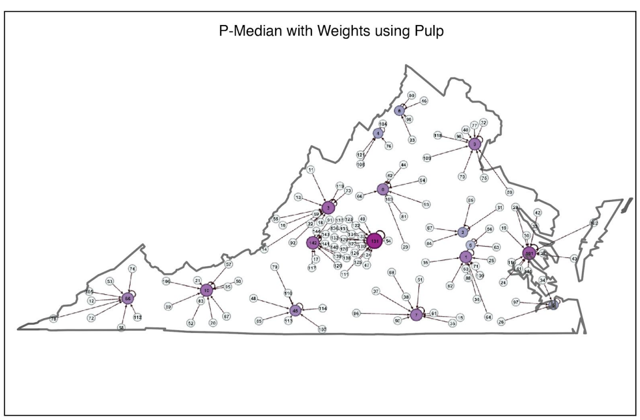

Figure 4. Weighted Python Solution

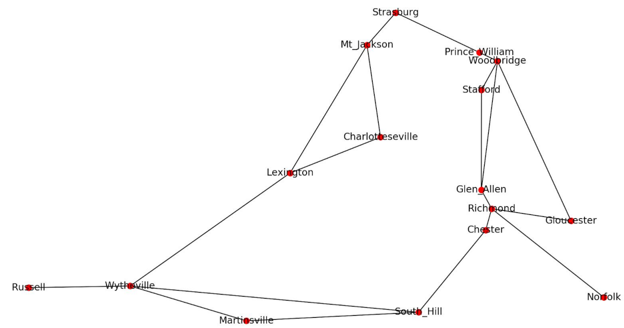

Figure 5. Weighted Python Network

5.2 ArcGIS Pro Method

The ArcGIS Pro method solutions differed in both the unweighted and weighted solutions. But the weighted solution matched two of the five locations that Tesla had chosen as seen in Table 1.

In both the Python and ArcGIS Pro formulations the solutions of the future Supercharger locations are closing gaps within the state making the distance traveled for demand nodes more feasible. As we move to Fig. 6, the solution is similar from the Python method in shortening the travel gaps of where demand nodes would have to travel long distances. But with Fig. 6, the ArcGIS Pro choices are dealing with much higher population areas. Which I believe would have chosen mostly high population nodes as future Supercharger locations. It makes sense to place the future Supercharger stations in the vicinity of the highest population counties such as Fairfax, and Newport News.

With Fig. 7 it displays the network of points for the weighted Supercharger points. It's interesting to note in all solutions there is no solutions in the center of Virginia, even in the Python method. This is most likely due to the extremely low demand to cater to in these counties. This route visualization in Fig 7. gives an idea of how one would travel through the nodes of Superchargers, and how there is not really a single long stretch to read one node to the next node.

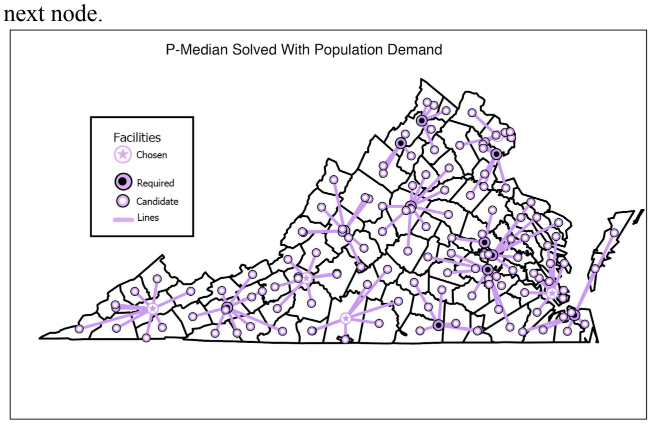

Figure 6. Weighted Solution and Demand Nodes

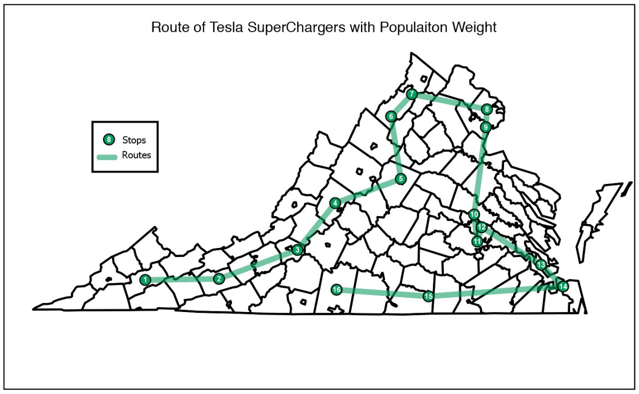

Figure 7. Network of route weighted solution

6. CONCLUSIONS

This research sought out to solve the P-median problem by optimally placing future Supercharging stations utilized by Tesla vehicles. The goal was to solve it using Python and comparing the results to a GIS software which was ArcGIS Pro. The Python solution did not match the same results as ArcGIS Pro. This can be attributed to how ArcGIS Pro formulates and calculates it's p-median problem. Along with the consideration of the how the road network is and the distances. With the Python method the origin-destination matrix was calculated to get Euclidean distance from points, whereas ArcGIS Pro used the road network or Manhattan distance of the origins and destination. The Python and ArcGIS Pro solutions both did not pick the same points Tesla did, but the ArcGIS Pro solution did get close by choosing 2 out of 5. Tesla has more intimate knowledge of their users, and the number of vehicles they sold and where. With this information their constraints and model will more optimal to suit the needs of the demands of the population in their formulation.

Even with just the distance constraint and population the chosen locations for each of the solutions are optimal to meet the demands of the constraints. With this the problem can be extended with new constraints and reworked to solve the problem at a smaller or larger scale.

7. FUTURE WORK

One problem that was not explored was a smaller scale solution to the P-median solution. It would be interesting to explore an individual county's charging station infrastructure and to solve a P-median problem there. An approach would be to have more constraints, such as limiting to a the power grid, potential locations that are convenient to users, and incorporate the flow of electricity of a city.

Another problem to explore is the capacitated p-median problem. Because each charging station has a limited amount of capacity (i.e. can have 4 cars charging at a time), you would need to que the amount of cars using them. Past research such as Menezes et al. (2014), solve the capiticted problem using schools as the facility. The schools have a limited capacity and the distance for students to travel to them is limited according to Mensez et al. (2014) formulation. This can be mimicked for a capacitated p-median problem because electric vehicles have a limited range they can travel and a limited capacity of users at a single station. A factor to consider is a constraint shortest path, to model how the cars travel and consume their energy to various stations (Baum et al. 2015). This is a complex model highlighted by Baum et al. (2015), but it might be the most realistic way to understand the flow of electric vehicles towards charging stations.

This problem would reflect how charging stations especially Tesla Superchargers function in reality. The ideal way to solve this is to gather data number of Tesla vehicles in long distance travel, information that is not currently publicly available. Along with how traffic flows in an area with Superchargers so we can understand peak times they are most utilized and underused to place future ones. Ideally this problem would involve the flow of vehicles to really reflect how the the capacity of charging stations would be consumed. The biggest barrier currently in future research is the lack of key data involving electric vehicles, that is most likely held by private corporation such as Tesla.

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